

PREDICTING OIL AND GAS BANKRUPTCIES IN THE TIME OF COVID-19

by

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## ABSTRACT

Stakeholders such as company management, shareholders, creditors, advisors, and employees are dependent on the success of the oil and gas exploration and production industry. The industry is a strong provider of jobs for the United States and Global Economy, and important for national defense. Given the industry importance, the ability to predict which companies will face financial distress and file for Chapter 7 or Chapter 11 bankruptcy is valuable. In today's environment, most oil & gas producers are facing distress via the external impact of low commodity prices. Therefore, this thesis formulates an accounting-based model, "L-Score", that accurately classifies a sample of 57 oil and gas producers as bankrupt or non-bankrupt from 2013 through 2019. The resulting L-Score is more effective than Altman's Z-Score by 170 bps for 2013 data, and 180 bps for 2014 data. The low-price environment, largely due to the global COVID-19 pandemic, is eerily consistent to the 2014 and 2015 oil price deterioration caused by a global supply glut. For that reason, a sample of 37 current oil and gas companies is used to predict bankruptcies into the future. The L-Score prediction model uses year-end 2018 financial data (because of the timing similarity with 2013) to predict which sample companies will or will not file for Chapter 11 bankruptcy from 2020 – 2025. The 2018 L-Score model both classifies and ranks the sample companies from "Most Unlikely" to file for bankruptcy to "Most Likely" to file for bankruptcy. The 2018 L-Score predictions have significant implications for stakeholders and can help all parties realize oncoming default/bankruptcy risk. These observations should lead to stakeholders proactively working together to solve and mitigate the necessary problems to remain solvent.

## **1. Introduction**

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### **1.1. Importance of Oil and Natural Gas Exploration**

Oil and natural gas exploration (“E&P”) is vital to the United States economy and employees. In 2017, oil and gas extraction contributed approximately \$188 billion to U.S. Gross Domestic Product (“GDP”) (U.S. Bureau of Economic Analysis, 2018). Oil and natural gas refined products heat American homes, fuel American vehicles, and light American backyard grills amongst many other uses. The E&P industry is also a stalwart provider of blue-collar jobs to working Americans. As of January 2020, the oil and gas extraction industry employed over 158,000 individuals (U.S. Bureau of Labor Statistics, 2020). Nowhere is the importance of oil and gas more evident than in the great American state of Texas. In 2017, Texas oil and gas extraction contributed over 6% of Texas’ GDP, or \$102 billion (U.S. Bureau of Economic Analysis, 2018). As of December 2019, the oil and gas extraction industry employed over 78,000 Texans (Federal Reserve Bank of Dallas, 2020).

Oil and gas exploration and production is also very important to equity and debt investors. As of January 31, 2020, 28 energy companies made up 3.9% of the S&P 500 index (S&P Dow Jones Indices, 2020). E&P shareholders include pension funds, retail investors, hedge funds, private equity firms, etc. Bondholders in E&P companies include pension funds, credit/special situations hedge funds, direct lending firms, etc.

Lastly, Oil and gas exploration and production is important for advisors including law firms, consultants, accounting firms, and investment banks. In 2019, ~\$9.8 billion in investment banking revenues came via energy and natural resources transactions (Investment Banking Scorecard,

2019). Overall, E&P is vital to major stakeholders including employees, communities, shareholders, creditors, and advisors.

## **1.2. Bankruptcy Impact**

Financial distress can lead to companies filing Chapter 7 or Chapter 11 bankruptcy. Although bankruptcy protection is necessary for many companies, it is typically not the best outcome for all stakeholders. In Chapter 7, liquidation occurs, employees lose their jobs, shareholders often get “wiped out”, and debt holders attempt to recover (or partially recover) principal. Chapter 11 cases are not as dire to all stakeholders but still likely include job loss, shareholder loss, Debtor-In-Possession (“DIP”) financing and debt-for-equity swaps or revised credit covenants in an attempt for bondholders to recover principal (Bankruptcy: What Happens When Public Companies Go Bankrupt, 2009). Corporate bankruptcies for oil and natural gas producers can be excruciating for all stakeholders.

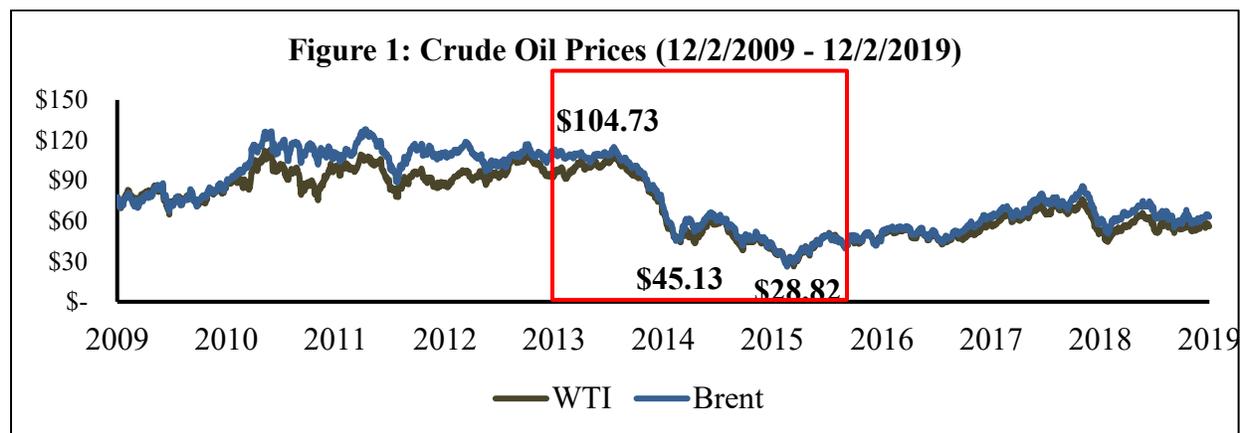
## **1.3. Foreseeing Financial Distress**

What if stakeholders could foresee impending financial distress years in advance? Equity and debt investors would steer clear of future losses. Employees would work for financially stable firms. However, the most critical beneficiary of foreseeing distress would be the company’s management. If an E&P company’s management envisions future financial distress it can hire lawyers, investment bankers, and consultants all specializing in restructuring. Pending concessions with creditors, the Company can restructure its balance sheet ahead of impending debt maturities and hefty interest payments that typically cause defaults. As well, the Company can restructure its operations for maximum efficiency in the long-term. In turn, the E&P Company would reignite

stakeholder interest from those vary same equity and debt investors, employees, and communities who are most devastated by corporate bankruptcies. **Answer:** If stakeholders can foresee impending financial distress, all parties can unite ahead of time to strengthen the company and avoid potential future liquidation.

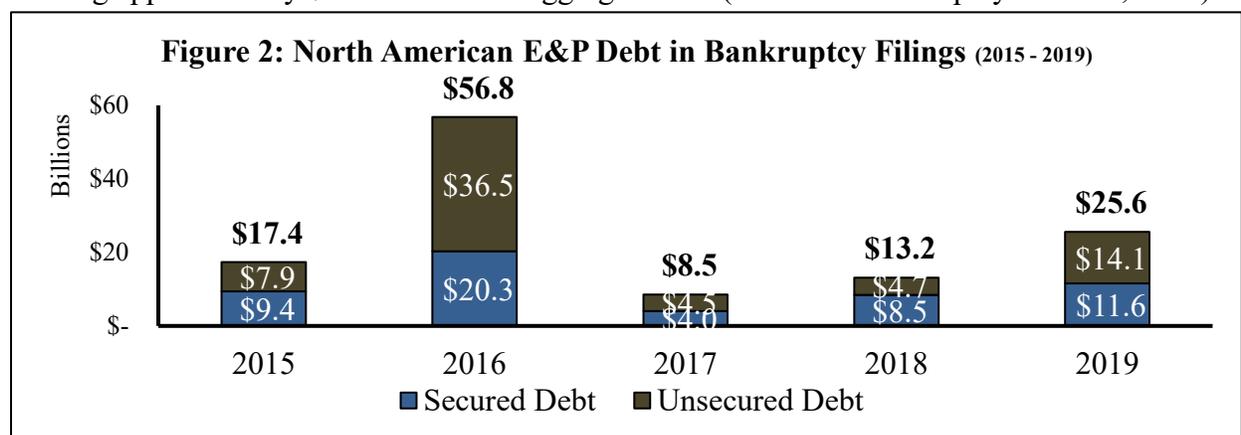
#### 1.4. E&P Bankruptcies Overview

Following a precipitous drop in crude oil prices in late 2014 and through 2015, E&P sector performance deteriorated – with many firms forced to file bankruptcy in 2015 and beyond.



Source: Federal Reserve Economic Data

Between 2015 and 2019, a total of 208 North American E&P companies filed for bankruptcy totaling approximately \$121.5 billion in aggregate debt (Oil Patch Bankruptcy Monitor, 2019).



Source: Oil Patch Bankruptcy Monitor, 2019

### **1.5. Previous Research Overview**

To date, bankruptcy prediction research is largely a result of static and hazard models for industrial firms based on accounting and/or market-based data (Altman, 1968) (Ohlson, 1980) (Shumway, 2001). Numerous researchers have adapted models for different industries including independent oil and gas producers (Platt et al., 1994) and financial services firms (Chava and Jarrow, 2004). However, no research has specifically developed a bankruptcy predictor model based on the recent surge in E&P bankruptcies. Although a bankruptcy predictor model has been developed specifically for independent oil and gas producers (Platt et al., 1994), it was built over 25 years ago prior to the U.S. shale and fracking boom.

### **1.6. Research Goal**

A bankruptcy prediction model that can evaluate companies forced to file amid recent oil price deterioration would be valuable for all stakeholders. With an updated and accurate North American E&P bankruptcy prediction model, investors and creditors would have improved decision-making and stakeholders can unite ahead of time to strengthen the company and avoid potential future liquidation. This thesis intends to add relevant variable(s) to past bankruptcy prediction models to produce an accurate static prediction model for today's large North American E&P companies. The model aims to predict which North American E&P companies face the largest distress risk in the current declining commodity price scenario driven by COVID-19.

## **2. Literature Review**

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Two broad types of existing bankruptcy prediction models exist: parametric and non-parametric models. Parametric models assume the parameters of a population function under a shape (Hoskin, 2012). Parametric bankruptcy prediction models primarily consist of accounting and market-based

variables. Non-Parametric models do not assume a distribution shape (Hoskin, 2012). Non-Parametric models typically consist of hazard, fuzzy, and hybrid models. For the purpose of this thesis, only parametric models will be examined.

## **2.1. Accounting-Based Models**

The baseline for all accounting-based default risk/bankruptcy prediction is Edward Altman's Z-Score. Using discriminant analysis, Altman arrived at a formula containing five weighted variables ranging from liquidity to profitability ratios. Altman analyzed 66 small manufacturing firms (33 bankrupt, 33 non-bankrupt as of 1966) from 1946-1965 to predict bankruptcy both one-year and two-years in advance. For the sample, the Z-Score was 95% accurate in classifying bankrupt/non-bankrupt one-year in advance and 72% accurate two-years in advance (Altman, 1968). With academic peers, Altman has continued to revisit the Z-Score both by changing variables (Altman et al., 1977) and changing samples (Altman et. al, 2000).

Following in Altman's footsteps, Ohlson created the O-Score and surmised that four basic factors should be analyzed when assessing one-year failure probability: 1) company size, 2) financial structure, 3) current liquidity, and 4) performance (Ohlson, 1980). The O-Score predicted with 96% accuracy for Ohlson's sample. However, Ohlson keenly noted that all bankruptcy prediction models are dependent on available information, industry, and time-period. Bankruptcy prediction models have disparate accuracy over time with changing external environments.

Until the 1970s, all mainstream bankruptcy prediction models had been based solely on "industrial" firms mostly in the manufacturing sector. Academics then expanded accounting-based

prediction models to other industries including railroads (1973), insurers (Pinches and Trieschmann, 1977), banks (Pettaway and Sinkey, 1980) and oil and gas (Platt et al., 1994),

## **2.2. Market-Based Models**

Market-based bankruptcy prediction models are primarily based on models such as Black Scholes (Black and Scholes, 1973), and Merton's distance to default model ("DD") (Merton, 1974). Specifically, Merton's DD has been used to forecast default probability using variables such as CDS spreads and bond yield spreads (Bharath and Shumway, 2008). Bharath and Shumway found that DD is a useful variable, but not significant in explaining default probability. As well, other researchers determined that accounting-based models fare better in the short-term, but lost relevance to market-based models over time (Reisz and Perlich, 2007).

On the other hand, numerous researchers found market-based models provided more significant results than accounting-based models. One study indicated that Black-Scholes and Merton models were better than Z -Score and O-Score at bankruptcy prediction (Hillegeist et al., 2004). Merton's DD model has also been utilized to evaluate default risk impact on equity returns (Vassalou and Xing, 2002), as well as analyze returns of financially distressed equities (Campbell et al., 2008).

## **2.3. Debt Maturities**

Since most bankruptcy prediction models either elicit accounting ratios or CDS spreads, etc., the impact of debt maturity timeline has been relatively under-studied. However, studies have shown that bankruptcy risk increases with shorter-term debt maturities (Kalaba et al., 1984), and that unfavorable private information will lead to a greater proportion of long-term debt issuances to

avoid short-term distress (Goyal and Wang, 2013). One study showed that traditional accounting-based models can merge with debt repayment schedule information to enhance bankruptcy prediction in the long-term (Philosohpov et al., 2008).

### **3. Methods & Results**

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#### **3.1 Sample Selection**

Given that large bankruptcies have a big impact on stakeholders, I selected a sample of large bankrupt and non-bankrupt E&P companies prior to the 2014 and 2015 oil price downturn. To analyze large independent oil and gas producers during the period before a commodity price downturn, specific criteria are selected. Sample companies must be public, North American, oil and gas exploration and production companies with greater than \$500 million in long-term debt (as of December 31, 2013). The Wharton Research Data Services (“WRDS”) database is utilized to identify sample companies. Specifically, the above criteria from Compustat on WRDS resulted in a total of 57 companies.

Each of the 57 companies are identified as either bankrupt or non-bankrupt. Specifically, if a company is classified as bankrupt it will have filed for bankruptcy from 2015 – 2019; otherwise, it will be classified as non-bankrupt. Haynes and Boones, LLP produces a quarterly informational report titled, “Oil Patch Bankruptcy Monitor”. This report is industry standard across bankruptcy reporting and its data is commonly featured in Wall Street Journal articles, etc. From this report, the following data is gathered from each of the 208 E&P bankruptcies from 2015 – 2019: 1) filing date, 2) court, 3) case-number, 4) debtor, 5) secured debt (\$ amt), 6) unsecured debt (\$ amt) (Oil Patch Bankruptcy Monitor, 2019). Using this data, 24 of the 57 sample companies are found to

have filed for bankruptcy from 2015 – 2019 and classified as “Bankrupt” (see Figure 3). 33 of the sample companies are classified as “Non-Bankrupt ” (see Figure 4).

Company Name	Filing Date	Long-Term Debt (as of 12/31/13)
Amplify Energy Corp	1/16/2017	792
Breitbart Energy Partners Lp	5/15/2016	1,890
Bonanza Creek Energy Inc	1/4/2017	509
Blue Ridge Mountain Resource	12/15/2015	876
Chaparral Energy Inc	5/9/2016	1,558
Cobalt Intl Energy Inc	12/14/2017	1,036
Ep Energy Corp	10/3/2019	4,421
Exco Resources Inc	1/15/2018	1,859
Frontera Energy Corp	4/29/2016	4,112
Halcon Resources Corp	7/27/2016	3,184
Jones Energy Inc	4/14/2019	658
Quicksilver Resources Inc	3/17/2015	1,989
Legacy Reserves Inc	6/18/2019	879
Linn Energy Inc	5/11/2016	8,959
Midstates Petroleum Co Inc	4/30/2016	1,701
Penn Virginia Corp	5/12/2016	1,281
Silverbow Resources Inc	12/31/2015	1,142
Sandridge Energy Inc	5/16/2016	3,195
Stone Energy Corp	12/14/2016	1,027
Sanchez Energy Corp	8/11/2019	593
Sabine Oil & Gas Corp	7/15/2015	1,243
Titan Energy Llc	7/27/2016	942
Ultra Petroleum Corp	4/29/2016	2,470
Vanguard Natural Resources	2/1/2017	1,008

Company Name	Long-Term Debt (as of 12/31/13)
Apache Corp	9,672
Anadarko Petroleum Corp	13,065
Antero Resources Corp	2,079
Chesapeake Energy Corp	12,917
Continental Resources Inc	4,714
Cabot Oil & Gas Corp	1,147
Concho Resources Inc	3,630
Denbury Resources Inc	3,261
Devon Energy Corp	7,956
Encana Corp	6,668
Eog Resources Inc	5,907
Eqt Corp	2,490
Enerplus Corp	977
Highpoint Resources Corp	979
Kosmos Energy Ltd	900
Laredo Petroleum Inc	1,052
Marathon Oil Corp	6,394
Murphy Oil Corp	2,937
Markwest Energy Partners Lp	3,023
Newfield Exploration Co	3,694
Northern Oil & Gas Inc	585
Occidental Petroleum Corp	6,939
Pdc Energy Inc	657
Pioneer Natural Resources Co	2,653
Qep Resources Inc	2,998
Resolute Energy Corp	737
Range Resources Corp	3,141
Sm Energy Co	1,600
Southwestern Energy Co	1,950
Unit Corp	646
Whiting Petroleum Corp	2,654
Wpx Energy Inc	1,916
Cimarex Energy Co	924

### 3.2 Measures

Because accounting-based methods of bankruptcy prediction have prevailed for over half a century and through multiple market cycles, Altman’s Z-Score is chosen as the initial independent variable (Altman, 1968). Altman’s Z-Score (below) is calculated for calendar years ending 2013 and 2014.

$$\text{Altman's Z-Score} = 1.2(a) + 1.4(b) + 3.3(c) + 0.6(d) + 1.0(e)$$

1.2	1.4	3.3	0.6	1.0
a	b	c	d	e
Working Capital / Total Assets	Retained Earnings / Total Assets	EBIT / Total Assets	Mkt Value of Equity / Total Liabilities	Sales / Total Assets

To achieve straightforward database identification, I identified all 57 sample companies’ GVKey’s. Using the GVKey’s on Compustat, all requisite data is downloaded for year-end 2013

and 2014 to calculate Altman’s Z-Score prior to distress in 2015 and beyond. Specifically, the following data is obtained: 1) Total Assets, 2) Long-Term Debt, 3) Liabilities, 4) Operating Income After Depreciation (AKA “EBIT”), 5) Preferred Stock, 6) Retained Earnings, 7) Revenue, 8) Working Capital, 9) Market Value of Equity. Using this data, the sample’s Z-Scores were calculated as of year-end 2013 and 2014.

### 3.3 Statistical Analysis

With the initial data, it is important to select the appropriate statistical analysis to be used. Because the dependent variable (bankruptcy) is binary, a typical OLS statistical analysis is unfit. At this point, I contacted renowned Associate Professor of Supply Chain Practice at TCU, Dr. David Weltman. After sharing the thesis’ goal with Dr. Weltman, he used his expertise in statistical analysis to provide a recommendation. Dr. Weltman recommended logistic regression analysis be performed. Performing a logistic regression shares the impact that one (or multiple) independent variables have on the sample’s bankruptcy prediction. To measure the results of logistic regression analysis, six baseline indicators were calculated: accuracy (% correct), specificity, sensitivity (recall), precision, F1, and multiple R squared (see Figure 6).

Figure 6: Formulas
<b>Accuracy (% correct) =</b> $\frac{\text{Number of sample companies classified correctly}}{\text{Number of sample companies}}$
<b>Specificity =</b> $\frac{\text{Number of non-bankrupt companies classified correctly}}{\text{Number of non-bankrupt companies}}$
<b>Sensitivity (recall) =</b> $\frac{\text{Number of bankrupt companies classified correctly}}{\text{Number of bankrupt companies}}$
<b>Precision =</b> $\frac{\text{Number of bankrupt companies classified correctly}}{\text{Number of bankrupt companies classified correctly} + \text{False positives}}$
<b>F1 Score =</b> $\frac{2 * (\text{Precision} * \text{Sensitivity})}{(\text{Precision} + \text{Recall})}$
<b>Multiple R Squared =</b> $1 - (\text{Unexplained Variation} / \text{Total Variation})$

Initial results for Z-Score bankruptcy prediction were very positive with accuracy peaking at 91.2% for 2014 Z-Score and 82.5% for 2013 Z-Score (see Figure 7). These initial results infer that Altman's Z-Score is still an excellent bankruptcy prediction model for oil and gas producers.

	Accuracy (%correct)	Specificity	Sensitivity (Recall)	Precision	F1 score	Multiple R Squared
<b>2013 Z-Score</b>	82.46%	81.82%	83.33%	76.92%	80.00%	35.67%
<b>2014 Z-Score</b>	91.23%	87.88%	95.83%	85.19%	90.20%	90.20%

### 3.4 Hypothesis

During my recent summer internship, I learned that a large indicator for restructurings is impending debt maturities. Companies with a large portion of long-term debt with maturities far into the future are only likely to default based on interest covenants such as interest coverage ratios. However, companies with near-term maturities are likely to default due to inability to pay down or refinance maturing debt. Therefore, I hypothesize that companies with a higher percentage of debt due in the near-term are more likely to file for Chapter 7 or Chapter 11 bankruptcy protection.

From this general hypothesis, I searched for independent variables that effectively measure near-term debt maturities. Compustat measures a company's amount of debt maturing in years one through five from the financial report date. Using this data, I calculate each sample company's amount of debt maturing for one, one to two, one to three, one to four, and one to five years. Amount of debt maturing is then calculated as a % of total liabilities. For both 2013 and 2014 data, % of debt maturing in: one, one to two, one to three, one to four, and one to five years was calculated. As such, 2013 debt maturity variables are implemented as independent variables along with 2013 Z-Score, and same with 2014 data. Using 2013 and 2014 Z-Score and maturities data, I performed two logistic regressions. The resulting output of this new analysis is named "L-Score."

### 3.5 Results

The results indicate that if a stakeholder performed an L-Score analysis in 2013, it would classify 84.2% of companies correctly (bankrupt or non-bankrupt). If a stakeholder performed an L-Score analysis in 2014, it would classify 93.0% of companies correctly. 2013 and 2014 L-Score classification are 170bps and 180bps more accurate than comparable Z-Score analysis, respectively. Any time the probability of predicting bankruptcy increases, this is exciting news for E&P stakeholders globally.

	Accuracy (%correct)	Specificity	Sensitivity (Recall)	Precision	F1 score	Multiple R Squared
2013 Z-Score	82.5%	81.8%	83.3%	76.9%	80.0%	35.7%
2013 L-Score	<b>84.2%</b>	<b>81.8%</b>	<b>87.5%</b>	<b>77.8%</b>	<b>82.4%</b>	<b>41.4%</b>
2014 Z-Score	91.2%	87.9%	95.8%	85.2%	90.2%	90.2%
2014 L-Score	<b>93.0%</b>	<b>90.9%</b>	<b>95.8%</b>	<b>88.5%</b>	<b>92.0%</b>	<b>67.3%</b>

The results are promising for bankruptcy prediction. Nevertheless, the analysis does not reject the null hypothesis. Notably, Altman's Z-Score is significant (p-value below .05) in for both 2013 (see Figure 9) and 2014 data (see Figure 10). However, none of the debt maturity variables were proven statistically significant. In the 2013 L-Score model, maturities within one-year were the most significant indicator other than Altman's Z-Score. While, in the 2014 L-Score Model, maturities within three-years were the most significant indicator other than Altman's Z-Score.

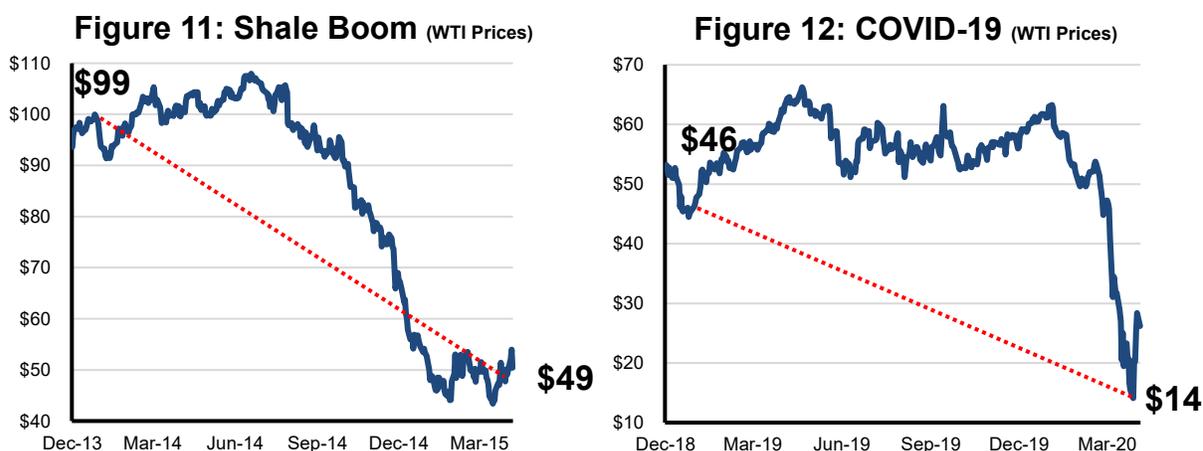
Predictor	Estimate	P-Value
Intercept	1.47199144	<b>0.095976011</b>
Z-Score	-1.619354147	<b>0.001757312</b>
1-Year	82.73044197	<b>0.29929269</b>
2-Year	-45.69795434	<b>0.279684601</b>
3-Year	1.923411203	<b>0.815089582</b>
4-Year	2.449926028	<b>0.728725968</b>
5-Year	1.708267748	<b>0.644449971</b>

Predictor	Estimate	P-Value
Intercept	2.89838983	<b>0.056195198</b>
Z-Score	-5.15751263	<b>0.00253411</b>
1-Year	3.198150531	<b>0.94159269</b>
2-Year	-8.707201205	<b>0.561815917</b>
3-Year	18.40861591	<b>0.137794345</b>
4-Year	0.805600402	<b>0.836327142</b>
5-Year	1.582855916	<b>0.598963538</b>

## 4. Discussion

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At this point in the work-process, the impact of COVID-19 became evident to the global economy and even more so to commodity prices. The L-Score model is premised on the ability to predict which companies will falter or survive in low commodity price scenarios. Although I was not expecting low commodity prices to come so soon – that is exactly what happened beginning in March 2020. West Texas Intermediate (“WTI”) price charts looked eerily similar to the last period of low commodity prices that began in late 2014.



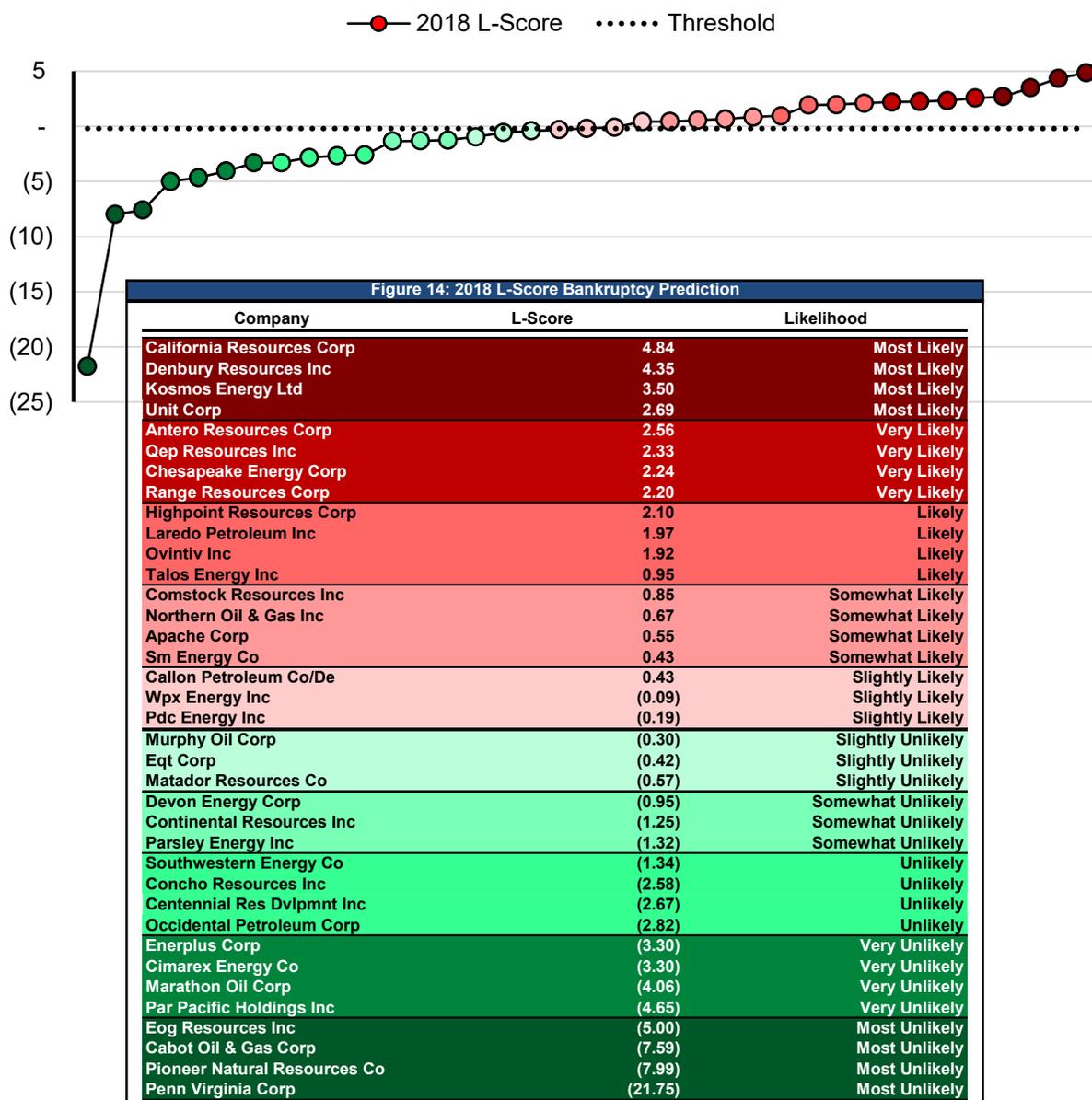
*Source: Federal Reserve Economic Data*

Because of the similar price circumstances, the 2013 L-Score model is uniquely positioned to predict which companies will file for Chapter 7/11 bankruptcy or will not in the next five years. According to the 2013 L-Score analysis, the model should predict future bankrupt/non-bankrupt classification at 84.2%.

To properly analyze the companies with L-Score, the same sampling process was re-performed. As of December 31, 2019, 37 Public, North American, Independent Oil and Gas producers with Long-Term Debt greater than \$500 million existed. Using this sample, each company’s L-Score was calculated with data as of December 31, 2018. In the 2013 L-Score analysis, the threshold for

bankruptcy prediction was (0.20). I.e. companies with L-Score’s greater than (0.20) are predicted to file for bankruptcy in the next five years. Whereas, companies with L-Score’s less than (0.20) are predicted to remain out of bankruptcy court for the next five years. Below, is a graph of the sample companies and their positioning (as of December 31, 2018) against the (0.20) threshold (see Figure 13). As well, each company’s L-Score is listed along with the likelihood the company will file for bankruptcy from 2020 to 2025 according to the L-Score model (see Figure 14).

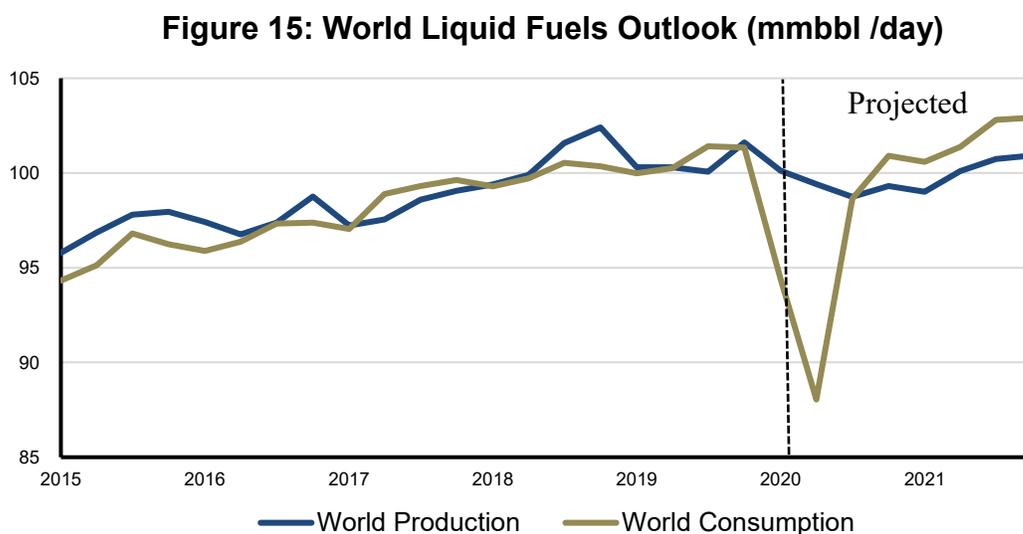
**Figure 13: L-Score Bankruptcy Prediction**



## 5. Implications

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This analysis is particularly well-timed given the current Spring 2020 market dynamics. Diminishing demand for oil and gas refined products amidst the COVID-19 pandemic has ruptured E&P company outlooks and fundamentals (see Figure 15).



*Source: Short-Term Energy Outlook, April 2020*

Below are implications for all major stakeholders including company management, shareholders, creditors, and employees. All E&P companies are facing struggles due to the direct impact of low commodity prices. For that reason, it is recommended that all 37 of the sample companies plan and act to mitigate default/bankruptcy risk. However, the L-Score's bankruptcy prediction provides express alert for the 19 sample firms predicted to file from 2020 – 2025. Specifically, stakeholders of firms classified as “Most Likely” or “Very Likely” to file for bankruptcy should be even more focused on proactive measures to avoid future distress and potentially bankruptcy.

## 5.1 Company Management

The L-Score results indicate that company management of the 19 predicted bankrupt firms need to “step up” to avoid future financial distress. Specifically, management of firms most at risk (California Resources, Denbury Resources, Kosmos Energy, and Unit Corp) should be actively targeting enhanced liquidity, negotiations with creditors, and hiring of restructuring advisors. Notably, company management for Unit Corp has already begun this process. As of April 21, 2020, Unit Corp has hired law firms: Opportune LLP and Vinson and Elkins LLP to likely prepare for a potential bankruptcy filing (Gladstone and Biswas, 2020).

As well, McKinsey and Co. lists ten tips to lead companies out of crisis (Yakola, 2014). C-Suite executives of high-risk firms should be utilizing tips including focusing on cash, building traction for change, retaining talented people, and involving the board of directors extensively. According to Bloomberg, California Resources executives have worked proactively for months to evaluate all “strategic options” (California Resources Said to Mull Bankruptcy, 2020). It is increasingly important for company management of high-risk E&P companies to understand the risk of future insolvency and proactively act.

## 5.2 Shareholders

The most obvious implication for equity investors is do NOT invest in E&P companies that are predicted to file for bankruptcy. According to the SEC, most Chapter 11 bankruptcies lead to the cancellation of existing shares (Bankruptcy: What Happens When Public Companies Go Bankrupt, 2009). Even if existing shareholders emerge from Chapter 11, they are likely to be very significantly diluted. Given that commodity prices are low, many investors are searching for

bargain E&P equities that are poised to rebound with future WTI price increases. However, this thesis' results indicate that equity investors should avoid firms predicted to seek bankruptcy protection and instead consider stronger (“Most Unlikely”) companies such as Penn Virginia Corporation, or Pioneer Natural Resources.

Nevertheless, existing shareholders of distressed E&P companies do not have the “luxury” of time-traveling and reconsidering their prior investment decisions. Shareholders have already been impaired significantly with equities such as California Resources (NYSE: CRC) down over 75% YTD 2020, as of April 24, 2020. Existing shareholders of companies predicted to file for Chapter 11 based on the L-Score should be seeking loss mitigation strategies. Bullish existing shareholders may believe bankruptcy is necessary, but that the firm will succeed in the long-term. If this is a shareholder's belief, buying distressed subordinated debt of the company may be a good strategy. If Chapter 11 occurs, the debt is likely to be swapped for equity and the existing shareholder can potentially profit in the long-term. However, bearish existing shareholders may want to sell out of their long position, and short the company in hopes of profiting until the company files for Chapter 11. Overall, existing shareholders or potential shareholders in E&P companies should be gravely concerned about the implications of this study and actively searching to mitigate losses.

### **5.3 Creditors**

Like shareholders, creditors can be divided into existing creditors and potential creditors. Existing creditors of distressed E&P companies will be seeking as much principal recovery as possible. Per the L-Score analysis, creditors of “Most Likely” and “Very Likely” companies should be actively negotiating for in or out-of-court debt restructurings. Franklin Resources is currently exhibiting

this strategy with its Chesapeake Energy investments. As of April 9, 2020, Franklin owned 12.4% of Chesapeake's equity, and ~\$9 billion in debt (Gladstone, 2020). Franklin has also hired law firm, Akin Gump Strauss Hauer & Feld LLP to advise it in debt restructuring negotiations (Gladstone, 2020). Existing creditors of the 19 sample companies predicted to file for bankruptcy should be considering debt restructurings and appropriate hiring of restructuring specialists.

Potential creditors of distressed E&P companies do not see demise, but rather opportunity. Notably, hedge funds and private capital firms with distressed debt strategies seek to make investments in companies that are likely to undergo bankruptcy or financial distress. Often, distressed debt securities trade well below principal, and notable funds including Oaktree Capital, Elliot Management, Solus Capital Management and Avenue Capital Group will buy the securities ("at pennies on the dollar") and become a major player in a future Chapter 11 bankruptcy. These firms are actively raising and deploying capital amidst the COVID-19 crisis – with Oaktree Capital seeking to raise a \$15 billion fund for this strategy (Oaktree Looks to Raise \$15 Billion, 2020). The L-Score analysis implies that distressed debt investors have many current opportunities to invest in E&P companies. For instance, per FactSet, California Resource's Unsecured Notes due 2024 were trading at \$.30 for a YTW of 39.22%, as of April 26, 2020. Debt investors can utilize the L-Score analysis to screen for Chapter 11 opportunities, as well as performing-credit opportunities for sample companies predicted to remain out of bankruptcy court.

#### **5.4 Employees**

Finally, E&P employees can benefit from L-Score analysis by seeking employment from well-positioned companies. According to the Texas Workforce Commission, ~2,500 Texas oil and gas

employees lost their jobs from April 13, 2020 to April 23, 2020 (Chapa, 2020). Although these numbers are disheartening, the L-Score analysis brings hope to laid-off oil and gas employees. Active E&P job applicants should be shunning the 19 E&P sample companies predicted to face bankruptcy. Instead job applicants should be applying to the 18 E&P sample companies that are better positioned for current market turmoil.

## **6. Conclusion**

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The outperformance of the resulting L-Score model is valuable. The addition of debt maturity data did lead to the model's improved performance against Altman's Z-Score. The results are exciting and should lead to the addition of maturity data into academic researchers' analysis of default/bankruptcy risk.

The compelling narrative of this thesis is the ability to predict future E&P bankruptcies using the L-Score model. Shareholders and creditors are known for gaining "any edge possible" to make the best investment recommendations. There is no doubt that an effectively designed model that ranks companies from "Most Unlikely" to "Most Likely" to file for bankruptcy is valuable information. Shareholders and creditors can use this model in conjunction with other credit models, credit reports, and credit ratings to inform their decision-making.

The surprise, of course, is the oil price deterioration that occurred while this research was progressing. This compelled the research question to adapt from: "which E&P companies are most at risk if a low-price environment occurs?" to "which E&P companies are most at risk NOW?". This exciting turn of events has increased both the importance and value of the L-Score model in the near-term. Certainly, financial stakeholders can benefit from this knowledge. More

importantly; however, blue-collar employees can use the L-Score model as a piece of informational data. The oil and gas industry is currently seeing one of the largest periods of job loss in history. It is my hope, that employees who experience job-loss will seek post COVID-19 employment with the stable, well-positioned companies that the L-Score predicts will not file for bankruptcy.

The original goal of the thesis was to build a model to predict which North American E&P companies face the largest distress risk in the current declining commodity price scenario. This was prefaced on the well-documented assumption that stakeholders who foresee impending financial distress, can unite to strengthen the company and avoid potential future liquidation. The L-Score model was successful in its 2013 and 2014 bankruptcy predictions. Given the oil price similarities between 2014/2015 and 2020, the external circumstances are analogous enough to estimate that the L-Score model will classify (bankrupt/non-bankrupt) in today's environment with similar success.

Now, it is up to the stakeholders to unite. I'm optimistic that management, shareholders, creditors, etc. of the 19 sample E&P companies predicted to file for bankruptcy can proactively act. Hopefully, these stakeholders will use all available information (including the L-Score) to realize their risk, realize the extent of their risk, and ultimately mitigate the risk. Certainly, a 100% classification rate for the new sample would be interesting for this thesis' success. However, it would save time, money, and jobs, if stakeholders use the L-Score model to identify risk, initiate action, and proactively restructure out-of-court. Therefore, a 0% future L-Score prediction rate is optimal for society.

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